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# Logit Demand Estimation Under Competitive Pricing Behavior: An Equilibrium Framework

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**D**iscrete choice models of demand have typically been estimated assuming that prices are exogenous. Since unobservable (to the researcher) product attributes, such as coupon availability, may impact consumer utility as well as price setting by firms, we treat prices as endogenous. Specifically, prices are assumed to be the equilibrium outcomes of Nash competition among manufacturers and retailers. To empirically validate the assumptions, we estimate logit demand systems jointly with equilibrium pricing equations for two product categories using retail scanner data and cost data on factor prices. In each category, we find statistical evidence of price endogeneity. We also find that the estimates of the price response parameter and the brand-specific constants are generally biased downward when the endogeneity of prices is ignored. Our framework provides explicit estimates of the value created by a brand, i.e., the difference between consumers' willingness to pay for a brand and its cost of production. We develop theoretical propositions about the relationship between value creation and competitive advantage for logit demand systems and use our empirical results to illustrate how firms use alternative value creation strategies to accomplish competitive advantage.

(*Demand Estimation; Logit; Endogeneity; Competitive Strategy*)

## 1. Introduction

The logit model of consumer choice has now become a standard tool for estimating the impact of marketing mix variables, such as price and sales promotions, on consumer brand choice. In marketing, the model has been extensively applied to optical scanning data collected from panels of households and to market share data (Guadagni and Little 1983, Cooper and Nakanishi 1988). The popularity of the model can be attributed to its ease of application and good predictive performance.

Researchers who estimate the logit model typically focus on consumer responses to firms' pricing and promotional decisions. In such work, prices and promotional activities are assumed to be *exogenously* determined. However, this assumption may not be justified in many cases. Product attributes, such as coupon availability and product image, impact consumer utility and

thus affect brand choices. These variables may not be observed by the researcher, but they may influence price setting by firms. For example, empirical evidence on coupon availability suggests a positive correlation between coupon availability and retail prices, both cross-sectionally and intertemporally (Vilcassim and Wittink 1987, Levedahl 1986). Similarly, national advertising by manufacturers, which can affect brand salience and image, is positively correlated with wholesale prices (Lal and Narasimhan 1996). From an econometric perspective, it follows that prices are likely to be positively correlated with error terms in the logit demand equations. When this happens, the difference in the market shares between two brands that is due to unobserved differences in product attributes is econometrically attributed to price. Since the brand with the higher market share could actually have a higher price

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than the brand with the lower market share, the estimate of the price response coefficient will be biased downward.

The purpose of this paper is to develop econometric estimates of a logit demand system under the assumption that observed prices and market shares are determined *endogenously* through equilibrium behavior. We estimate a logit model for two product categories: yogurt and catsup. For both categories, a statistical test of exogeneity of prices rejects the null hypothesis that prices are exogenous. Comparisons with logit demand estimates when price endogeneity is ignored reveals that the estimates of the price response parameter are biased downward in both categories. This is consistent with the intuition developed above and with the results of other studies discussed later.

Several scholars have recently pointed out the importance of accounting for the endogeneity of prices in a discrete choice econometric framework. Berry (1994), for example, argues that "The endogeneity of prices that follows from the presence of unobservable product characteristics is not just an econometric quibble." He uses Monte Carlo methods to show that estimation methods that ignore the endogeneity of prices can be "severely misleading." Similar to our empirical results, he finds that ignoring simultaneity results in a downward bias in both the estimates of the price response parameter and the estimates of brand-specific constants.<sup>1</sup> Berry et al. (1995) estimate discrete choice models in the automobile market and find that by ignoring the endogeneity of prices, price response coefficients are only about half as large as they are when instrumental variables techniques are employed to account for endogeneity. Villas-Boas and Winer (1995) also consider the problem of endogenous prices in a logit framework. They use lagged price and lagged market share as instruments for price and estimate the logit model using household-level panel data. They, too, find that ignoring the endogeneity of prices results in a downward bias in the estimated price response coefficient.

Several key analytical issues arise in an attempt to estimate logit models with endogenous prices. The first

is how to deal with the problem of endogeneity (e.g., simultaneity bias). One approach is to use instruments for prices. Villas-Boas and Winer (1995) and Berry et al. (1995) use this approach. An alternative is to assume that prices are determined by an equilibrium model. Gasmi et al. (1992), Kadiyali et al. (1996), and Roy et al. (1994) follow this approach in their analysis of competitive behavior in the soft drink, laundry detergent, and automobile markets, respectively. Unlike our work, however, these studies estimate a linear demand structure rather than a logit demand structure.

In this paper, we employ an equilibrium framework. We assume that manufacturers and retailers act as profit-maximizing Nash price setters; therefore, wholesale prices and retail margins are determined endogenously in the model. We then simultaneously estimate the logit demand equations and pricing equations implied by the Nash equilibrium conditions. A valuable by-product of this approach is that we obtain estimates of consumer willingness to pay associated with each brand in a product category. The measurement of the utility that consumers attach to brands has been done in a variety of ways in the marketing literature. These include self-reported measures of attitudes or preferences obtained through surveys or conjoint analysis, as well as estimates of brand values from market-place data (Kamakura and Russell 1993). An advantage of estimating the logit model in an equilibrium framework, however, is that we also obtain estimates of each brand's marginal cost, which then allows us to compute the *value created* (i.e., willingness to pay minus marginal cost) for each brand in a product category. This makes our analysis directly relevant to modern value-based theories of business strategy (Besanko, Dranove, and Shanley 1996; Brandenberger and Stuart 1996). We derive theoretical propositions that show a positive relationship between a brand's value creation and its equilibrium market share and operating profit. Thus, the market share leader in the category must also be the value-creation leader. Because value-created is willingness to pay minus cost, the brand with the highest value creation need not have either the highest willingness to pay or the lowest cost.

A second issue that must be addressed is potential aggregation bias that arises from the use of store-level rather than household-level data. We use store-level

<sup>1</sup> We also find a downward bias in the brand-specific constants in both the yogurt and catsup categories.

data because our equilibrium pricing equations relate the retail price of each brand to its market share. This occurs because for the product categories we study, retail prices and promotional conditions at a given store each week are the same for all consumers, thereby eliminating the risk of aggregation bias (Allenby and Rossi 1991).

A third issue that must be addressed is that the standard logit model implies potentially unrealistic substitution patterns between brands in a product category. To address this issue, we also determine equilibrium pricing conditions for the nested logit model, which is known to be less restrictive than the standard logit model (Maddala 1988).

The remainder of this paper is organized as follows. Section 2 presents the basic logit model and derives and characterizes the Nash equilibrium in prices in a market with logit demand. Section 3 discusses model specification and estimation issues. Section 4 discusses the data and presents empirical results for two categories. Section 5 explores the subject of value creation and competitive advantage. Section 6 concludes.

## 2. Oligopolistic Competition with Logit Demand

The standard logit formulation assumes that each household faces a choice among a given set of  $I$  brands. In addition, a household has the option to not purchase any of the brands, i.e., to choose the no-purchase alternative. Each brand  $j$  is characterized by a vector  $X_{jt}$  of observable (to the firm and the econometrician) product attributes and marketing variables (e.g., store display and advertising activity on behalf of the brand), the mean utility  $\xi_{jt}$  that each consumer obtains from unobservable (to the econometrician but not the firm) product attributes, and a price  $p_{jt}$ . For a particular household  $h$ , the utility  $u_{hjt}$  of the  $j$ th brand on purchase occasion  $t$  is given by

$$u_{hjt} = \beta_{0j} + \beta X_{jt} - \alpha p_{jt} + \xi_{jt} + \epsilon_{hjt}, \quad j = 1, \dots, I,$$

where  $\beta$  is a vector of the response coefficients for the observable product attributes;  $\beta_{0j}$  is a brand-specific intercept that indicates intrinsic preferences for brand  $j$ ;  $\alpha$  is the price response coefficient; and  $\epsilon_{hjt}$  is household  $h$ 's idiosyncratic preference for brand  $j$  on purchase occa-

sion  $t$ . Each household  $h$  is assumed to draw  $I + 1$  idiosyncratic preferences  $\epsilon_{h0t}, \epsilon_{h1t}, \dots, \epsilon_{hIt}$  from an extreme value distribution with location parameter 0 and scale parameter 1. A household then chooses the brand  $j$  that attains the maximal value in the set  $\{u_{h0t}, u_{h1t}, \dots, u_{hIt}\}$ , where  $u_{h0t} = \epsilon_{h0t}$  is the utility of the no-purchase alternative. If  $u_{h0t}$  is maximal, the household does not purchase in period  $t$ .

The inclusion of the mean utility  $\xi_{jt}$  from unobservable product attributes follows Berry's (1994) formulation of the discrete choice model. This term will serve as the econometric error in the empirical specification of the demand equations. Note that  $\xi_{jt}$  differs from the idiosyncratic valuations  $\epsilon_{hjt}$  in that  $\xi_{jt}$  is brand-specific but not consumer-specific. Unlike the realizations of  $\epsilon_{hjt}$ ,  $\xi_{jt}$  is observed by the firms and thus directly incorporated into price setting behavior. A natural interpretation of  $\xi_{jt}$  is the variation in preferences for brands that is induced by coupon availability and manufacturers' advertising, as discussed in the introduction.

In the subsequent analysis, for convenience we define

$$v_{jt} \equiv \frac{\beta_{0j} + \beta X_{jt} + \xi_{jt}}{\alpha}, \quad j = 1, \dots, I. \quad (1)$$

$v_{jt}$  is the "average" consumer's maximum willingness to pay for brand  $j$  on purchase occasion  $t$ . Given this,  $v_{jt} - p_{jt}$  represents the consumer surplus for brand  $j$  for the average consumer at time  $t$ , and if the cost of producing brand  $j$  is  $c_{jt}$ ,  $v_{jt} - c_{jt}$  is the value created by brand  $j$  for the average consumer at time  $t$ . Later in the paper, we derive results relating equilibrium market shares and profitability to a brand's value created.

At  $t$ , the expected market demand  $D_{jt}$  for brand  $j$  will equal the probability that any given household purchases brand  $j$  times the total number  $H$  of households, i.e.,  $D_{jt} = s_{jt}H$ , where

$$s_{jt} \equiv \frac{e^{\alpha(v_{jt}-p_{jt})}}{\sum_{i=1}^I e^{\alpha(v_{it}-p_{it})} + 1}, \quad j = 1, \dots, I. \quad (2)$$

For econometric estimation, it will be convenient to express the market share equations in (2) in logarithmic form and differences with respect to the share  $s_{0t}$  of the no-purchase alternative:

$$\ln(s_{jt}) = \ln(s_{0t}) + \beta_{0j} + \beta X_{jt} - \alpha p_{jt} + \xi_{jt}, \\ j = 1, \dots, I. \quad (3)$$

As will be shown below,  $\xi_{jt}$  will be correlated with  $p_{jt}$ , which gives rise to simultaneity bias in standard logit estimation.

To develop a specification for equilibrium retail prices that can be estimated econometrically, we now derive the Nash equilibrium wholesale and retail prices in a market characterized by logit demand. We consider a setting with  $M$  manufacturers who set wholesale prices. We index brands under the assumption that manufacturer 1 produces a set of brands  $I_1 = \{1, \dots, i_1\}$ ; manufacturer 2 produces a set of brands  $I_2 = \{i_1 + 1, \dots, i_2\}$ , and so forth. Each manufacturer sets the wholesale price  $w_j$  of each brand it produces.

Manufacturers are assumed to sell through retailers who set the retail price  $p_j$  of each good  $j$ . Each retailer is assumed to be a "local monopolist"; that is, we do not explicitly consider price competition among retailers. This assumption is broadly consistent with the evidence reported by Slade (1995). She interviewed grocery-chain managers who reported that over 90 percent of households *do not* engage in comparison shopping across stores to seek out the lowest-price item. She also finds that for the saltine cracker product category, sales within one chain are unaffected by prices within other chains. Supporting evidence is also available in Walters and Mackenzie (1988) who empirically examined the impact of loss-leader pricing and other promotions on store sales and profits. Their data covered *all* grocery items sold by two supermarkets. Their results indicate that price specials and double coupon promotions had no effect on store traffic. Moreover, only one of eight loss-leader categories examined significantly influenced store traffic.

We use the *vertical Nash* model in Choi (1991) to describe the non-cooperative interactions between oligopolistic manufacturers and the common retailer. In this model, manufacturers and retailers move simultaneously: manufacturers choose the wholesale prices  $w_j$  of their brands (taking as given the retail margins of their brands and the retail prices  $p_k$  of competing brands), while the retailer determines the retail prices (taking the wholesale prices as given). The Nash equilibrium occurs when each manufacturer's wholesale prices are a best reply to the retail prices of competitors' brands and to the retail margins chosen by the retailer for its own brands, and when the retailer's prices of all

brands are a best reply to the wholesale prices chosen by manufacturers. Choi suggests that this model is most applicable in settings where manufacturers and retailers have approximately equal power within the vertical channel and manufacturers can observe competitors' retail prices more easily than their wholesale prices.

To develop a characterization of the equilibrium, consider the profit-maximization problem of manufacturer  $m$ . It chooses its wholesale prices  $w_i, i \in I_m$  to maximize

$$\Pi_m \equiv \sum_{i \in I_m} (w_i - c_i)s_i H$$

where  $c_i$  is the marginal cost of producing brand  $i$ , and  $s_i$  is given by Equation (2).

The first-order conditions for manufacturer  $m$ 's profit maximization problem are:

$$\frac{\partial \Pi_m}{\partial w_j} = \sum_{i \in I_m} (w_i - c_i) \frac{\partial s_i}{\partial p_j} H + s_j H = 0, \quad j \in I_m. \quad (4)$$

Expression (4) is derived under the (Nash) assumption that a manufacturer takes the retail *margins*  $p - w$  of its own brands and the retail prices of other brands as given.<sup>2</sup> From Equation (2), it follows that:

$$\frac{\partial s_j}{\partial p_j} = -\alpha s_j(1 - s_j), \quad \frac{\partial s_j}{\partial p_k} = \alpha s_j s_k, \quad j \neq k.$$

Given these expressions, (4) can be shown to imply

$$w_j = c_j + \frac{1}{\alpha} \frac{1}{(1 - S_m)}, \quad j \in I_m, \quad (5)$$

where  $S_m \equiv \sum_{i \in I_m} s_i$  is manufacturer  $m$ 's unconditional market share.

The retailer's problem is to set retail prices  $p_1, \dots, p_I$  on the full set of  $I$  brands to maximize the retail profit  $\Pi^R \equiv \sum_{j=1}^I (p_j - w_j)s_j H$  from the product category. The profit-maximizing retail price for brand  $j$  can be shown to equal

$$p_j = w_j + \frac{1}{\alpha} \frac{1}{s_0}, \quad j = 1, \dots, I, \quad (6)$$

where, recall,  $s_0$  is the share of households which elect not to purchase any brand.

<sup>2</sup> In effect, the vertical Nash model implies  $dp_j/dw_j = 1$ , and  $dp_j/dw_k = 0$ , for  $k \neq j$ .

At a full Nash equilibrium between manufacturers and the retailer, Conditions (5) and (6) hold for all brands in the market. The full set of Nash equilibrium retail prices and market shares (denoted by \*) can thus be characterized as follows:<sup>3</sup>

$$p_j^* = c_j + \frac{1}{\alpha} \frac{1}{(1 - S_m^*)} + \frac{1}{\alpha} \frac{1}{s_0^*}, \\ j \in I_m, \quad m = 1, \dots, M, \quad (7)$$

$$S_m^* \equiv \sum_{i \in I_m} s_i^* = \frac{\sum_{i \in I_m} e^{[\alpha(v_i - c_i) - (1/(1 - S_m^*)) - 1/s_0^*]}}{\Omega}, \\ m = 1, \dots, M, \quad (8)$$

$$s_0^* = \frac{1}{\Omega}, \quad (9)$$

where

$$\Omega \equiv \sum_{i \in I_1} e^{[\alpha(v_i - c_i) - (1/(1 - S_1^*)) - 1/s_0^*]} \\ + \dots + \sum_{i \in I_M} e^{[\alpha(v_i - c_i) - (1/(1 - S_M^*)) - 1/s_0^*]} + 1. \quad (10)$$

Note that the unobserved product attribute  $\xi_k$  for brand  $k$  influences equilibrium prices and market shares through its effect on the willingness to pay  $v_k$ . As discussed previously, simultaneity bias in logit estimation arises when  $\xi_k$  and the price of brand  $k$  are positively correlated. This occurs if the equilibrium price  $p_k^*$  increases in  $\xi_k$ , i.e.,  $(dp_k^*/d\xi_k) > 0$  for any brand, as shown below.<sup>4,5</sup>

**PROPOSITION 1.** *An increase in unobserved (to the econometrician) product attributes  $\xi_k$  for any brand  $k$  increases the equilibrium price  $p_k^*$  of that brand; i.e.,  $dp_k^*/d\xi_k > 0$ .*

Although this proposition applies to manufacturers that produce either a single brand or multiple brands, the intuition for the proposition is easiest to describe for the case of single-brand firms. In that setting, profit-maximizing behavior by the manufacturer gives rise to

<sup>3</sup> Equation (7) is obtained by substituting Equation (5) into Equation (6). Substituting Equation (7) into Equation (2) gives rise to Equation (8).

<sup>4</sup> The proofs of all propositions are available in Besanko et al. (1996).

<sup>5</sup> Chintagunta and Rao (1996) prove a similar result.

the traditional “inverse elasticity rule” whereby a brand’s equilibrium wholesale margin is proportional to the inverse of its “own” price elasticity of demand. Profit-maximizing behavior by the *retailer* gives rise to a multi-product version of the inverse elasticity rule whereby the retail margin for a brand depends on its “own” price elasticity and the cross-price elasticities of that brand with other brands in the product category. In the logit model, a brand’s “own” price elasticity of demand decreases as its market share goes up, so a brand’s profit-maximizing wholesale margin is an increasing function of its market share. For related, though less intuitively obvious reasons, the retailer’s profit-maximizing retail margin is also an increasing function of the brand’s market share. Any exogenous change that increases consumer willingness to pay for the brand will increase the brand’s market share and will induce the manufacturer to raise the wholesale price and the retailer to raise the retail margin.

### 3. Model Specification and Estimation

We now convert the model of oligopolistic competition described in the previous section into an empirically testable specification. The model will be estimated for two product categories: yogurt and catsup. To simplify the exposition, the specification will be developed for the case in which each manufacturer produces a single brand.<sup>6</sup> For single-brand manufacturers, the equilibrium conditions in (7)–(10) reduce to

$$p_j^* = c_j + \frac{1}{\alpha} \frac{1}{(1 - s_j^*)} + \frac{1}{\alpha} \frac{1}{s_0^*}, \quad j = 1, \dots, I, \quad (7a)$$

$$s_j^* = \frac{e^{[\alpha(v_j - c_j) - (1/(1 - s_j^*)) - (1/s_0^*)]}}{\Omega}, \quad j = 1, \dots, I, \quad (8a)$$

$$s_0^* = \frac{1}{\Omega}, \quad (9a)$$

$$\Omega \equiv \sum_{i=1}^I e^{[\alpha(v_i - c_i) - (1/(1 - s_i^*)) - (1/s_0^*)]} + 1. \quad (10a)$$

To move from the equilibrium pricing condition in

<sup>6</sup> The extension to the case of multi-brand manufacturers using the equilibrium conditions in (7)–(10) is straightforward.

(7a) to the pricing equation that we estimate, we assume that marginal cost is a brand-specific function of factor prices:

$$c_j = \gamma_{0j} + \gamma_j W, \quad (11)$$

where  $\gamma_{0j}$  is a brand-specific constant;  $\gamma_j$  is a vector of cost parameters, and  $W$  is a vector of cost shifters. The cost shifter variables used are ingredients prices, container prices, and labor wage rates. These variables are described in greater detail in the next section. The parameters of the cost function are assumed to be brand-specific.

Substituting (11) into (7a), we obtain the following pricing equations:

$$p_{jt} = \gamma_{0j} + \gamma_j W_t + \frac{1}{\alpha} \frac{1}{1 - s_{jt}} + \frac{1}{\alpha} \frac{1}{s_{0t}} + \tau_{jt},$$

$$j = 1, \dots, I, \quad (12)$$

where  $\tau_{jt}$  is an error term. The demand equations to be estimated are given in (3):

$$\ln(s_{jt}) = \ln(s_{0t}) + \beta_{0j} + \beta X_{jt} - \alpha p_{jt} + \xi_{jt}, \quad j = 1, \dots, I.$$

For econometric estimation, the  $I$  market share equations above along with the  $I$  pricing equations in (12) are treated as a system of  $2I$  non-linear simultaneous equations. The structural parameters to be estimated are: the price response coefficient  $\alpha$ ;  $I$  brand-specific constants  $\beta_{0j}$ ,  $j = 1, \dots, I$ ; a vector  $\beta$  of response coefficients of the demand-side covariates  $X_{jt}$ , which in this analysis are feature and display activity;  $I$  brand-specific constants  $\gamma_{0j}$  in the marginal cost functions;  $I$  vectors of cost shifter parameters  $\gamma_j$ . In this analysis we use three cost shifters: wages, ingredient prices, and container prices, so  $\gamma_j = (\gamma_{1j}, \gamma_{2j}, \gamma_{3j})$ . Since several parameters appear in more than one equation, we impose cross-equation restrictions in estimation.

It is well known that the standard logit model has potentially unrealistic implications for substitution patterns across brands within the category. Specifically, in the standard logit model, all information pertaining to substitution patterns between two brands is absorbed in the market shares of these brands. Thus, given the market shares, the cross-price elasticities of demand do not depend on observable product differences. This as-

sumption may not be especially restrictive in a product category such as yogurt in which there are no natural subsets of "close" brands, but it may be very restrictive in a category such as catsup in which product offerings differ by both brand name and by size. In this case, consumers may regard all brands within a particular size as "closer" together than brands available in different sizes. A natural question is whether endogeneity biases arise in a model that allows for more reasonable substitution patterns.

To address this question, in addition to estimating the model in the catsup category using the standard logit demand structure, we also estimate it using the generalized extreme value (GEV) or nested logit structure. The nesting structure assumes a size-primary market. That is, a consumer first chooses whether to purchase and if so, what size catsup to buy. Given a size, the consumer then chooses which manufacturer's brand to buy.<sup>7</sup> In our data, virtually 100 percent of all sales in the 44 ounce and 28 ounce size categories were of Heinz products, so the choice to purchase in these categories implies that the consumer will choose a Heinz brand. Given that a consumer chooses the 32 ounce size category, however, he has a choice between the Hunts and the Heinz 32 ounce brand. The demand and pricing equations for the nested logit are developed in the Appendix.

#### 4. Empirical Analyses

The data on prices, market shares, feature, and display activity were collected by the AC Nielsen Company in Springfield, Missouri using store check-out scanners. For model estimation, we pool weekly sales data for nine stores belonging to a single chain that characterizes itself as an "Everyday Low Price" (EDLP) chain. The data for the two product categories, yogurt and catsup, are for a 102 week period in 1986–1988.

<sup>7</sup> Although we report empirical results for a size-primary model, we also estimated a brand-primary model in which a consumer first chooses a brand, and then chooses a size. In a brand-primary model, the amount of catsup a consumer buys is conditional on which manufacturer's brand it chooses. Estimation of the brand-primary model results in an estimate of the "within group" correlation of utility levels that is less than zero, a result inconsistent with the hypothesis of nesting. For this reason, this section reports only the results for the size-primary model.

Weekly shares of the “no purchase” alternative are unavailable in the store sales data. Hence we use data on store visits made by a panel of 2,500 households to obtain estimates of the share of the “no purchase” alternative. AC Nielsen reports that these panelists made over 80 percent of their purchases in the stores included in the store data. In each week, for each of the nine stores of interest, we compute the proportion of panelist households’ visits to that store that did not result in a purchase in the category of interest. These shares are then merged with the brand shares obtained from the store data.

The price variables used in the estimation for each product category are retail shelf prices per ounce. These shelf prices are net of in-store promotional price cuts. We also use feature and display activity as covariates in the demand equations.<sup>8</sup>

For both product categories, we obtained factor price data for labor and for a key ingredient in the production process of the product. For catsup, we also obtained prices of container materials. Labor prices come from the Bureau of Labor Statistics (BLS) publication *Employment and Earnings*. The BLS provides monthly data on average hourly earnings of production workers by 3 digit or 4 digit SIC code. For each product category, we identified the narrowest SIC category which included the product category in question (SIC 202, dairy products, for yogurt; SIC 2033, canned fruits and vegetables, for catsup). Monthly data on ingredient and container prices was obtained from producer price indexes compiled by the BLS. Ingredient prices are the producer price indexes for fluid milk (yogurt) and tomatoes (catsup). The container price for catsup is the producer price index for glass food containers. We used the linear filtering process employed by Slade (1995) to convert monthly data to weekly data. The input price  $W_t$  in week  $t$  was assumed to be the value of the input price in the corresponding month. Then, we smoothed the series as follows:

$$W_t^S = 0.25W_{t-1} + 0.50W_t + 0.25W_{t+1}.$$

In each product category, the brands included in the analysis constituted at least 70 percent of category vol-

<sup>8</sup> However, there is no display activity on any brand in the yogurt category.

ume. Each brand in the yogurt category is manufactured by a different firm. Dannon, Yoplait, and Weight Watchers are national brands, while Hiland is a regional brand. In catsup, there are three sizes of the major brand Heinz, and the most popular size (32 ounce) of the largest competitor, Hunts.

Table 1 presents descriptive statistics for both product categories. It also presents summary information on the factor prices used in the analysis. In yogurt, Dannon is the dominant market-share leader, and has the second highest retail price. Weight Watchers is priced below the other brands in the market. In catsup, Heinz commands an 82 percent market share. The 32 ounce sizes of both Heinz and Hunts have nearly identical prices, although Heinz has more display and feature activity than Hunts.

Because model estimation requires taking the log of the brand share, we had to find a way to deal with store-weeks with zero shares. Cooper and Nakanishi (1988) evaluate two alternative ways of dealing with zeros in market-share models: (1) assign arbitrarily small values to zero shares; (2) delete store-weeks with zero shares. The first procedure amounts to assigning a large negative value to  $\log(0)$ , which tends to bias the estimated parameter values upwards (in absolute magnitude). While deletion of zero share observations tends to bias the estimated parameters in the direction of smaller absolute values, they argue that the biases are far less. We delete observations where at least one item has a zero-share, resulting in 703 and 724 observations for the yogurt and catsup data, respectively.

The system of non-linear simultaneous equations consisting of the demand functions in (3) and the equilibrium pricing functions in (12) is estimated using non-linear Three Stage Least Squares (3SLS). The 3SLS estimator provides consistent estimates of the parameters (Amemiya 1985). The exogenous variables in the system (display, feature, and factor prices) serve as instruments.<sup>9</sup>

The assumption that prices are endogenous is central to the model formulation. To test this assumption,

<sup>9</sup> An alternative estimator we considered was the non-linear Full Information Maximum Likelihood (FIML) estimator. The FIML estimator is consistent if the true distribution of the errors is normal, but is generally inconsistent if it is not normal (Amemiya 1985). The 3SLS estimator does not suffer from this restriction.

Table 1 Descriptive Statistics of Data

Items	Brand Shares (Conditional)	Avg. Price (Cents/Oz.)	Display (% Store-Weeks)	Feature (% Store-Weeks)
<b>Yogurt*</b>				
Dannon	42.82	8.03	0	4.6
Yoplait	23.05	10.39	0	5.8
Weight Watchers	23.91	5.24	0	1.7
Hiland	10.22	7.73	0	3.8
<b>Catsup**</b>				
Heinz 32 oz.	43.4	4.24	10.1	6.5
Hunts 32 oz.	17.8	4.24	1.1	1.8
Heinz 28 oz.	32.6	5.04	9.3	3.7
Heinz 44 oz.	6.1	4.74	0	0
<b>Costs</b>				
	Avg. Hrly Earnings of Prod. Workers (\$)	Material Cost Index for Primary Ingredient	Material Cost Index for Container	
Yogurt	9.71	103.95	N.A.	
Catsup	8.25	99.55	111.08	

\* Share of "No Purchase" is 83.1%.

\*\* Share of "No Purchase" is 82.4%.

we adapt the specification test proposed by Hausman (1978). Under the null hypothesis that prices are not endogenous, the (non-linear) SUR estimator  $\hat{\theta}_{\text{SUR}}$  provides consistent estimates of the demand parameters  $\theta \equiv (\alpha, \beta_{01}, \dots, \beta_{01}, \beta)$  (Gallant 1975). Since the market shares of brands necessarily sum to one, the error terms of the demand equations are correlated; hence, SUR is preferred over OLS. The SUR estimator, however, is inconsistent under the alternate hypothesis that prices are endogenous. The two-stage least squares (2SLS) estimator  $\hat{\theta}_{\text{2SLS}}$ , by contrast, is consistent both under the null and the alternate hypotheses (Amemiya 1985). Further, since  $\hat{\theta}_{\text{SUR}}$  is also asymptotically efficient,  $(V_{\text{2SLS}} - V_{\text{SUR}})$  is nonnegative definite, where  $V$  is the variance-covariance matrix. Under these assumptions, Hausman shows that the test statistic

$$(\hat{\theta}_{\text{2SLS}} - \hat{\theta}_{\text{SUR}})'(\hat{V}_{\text{2SLS}} - \hat{V}_{\text{SUR}})^{-1}(\hat{\theta}_{\text{2SLS}} - \hat{\theta}_{\text{SUR}})$$

is asymptotically chi-squared distributed with  $n$  degrees of freedom, where  $n$  is the dimensionality of  $\theta$ . In both product categories, comparison of SUR with 2SLS estimates using the Hausman test leads to the rejection ( $p$

< 0.01) of the null hypothesis that prices are exogenous. This suggests that the estimates of the price response coefficients using SUR are likely to be biased.

Tables 2 and 3 summarize parameter estimates, standard errors, and fit statistics for the two product categories. In the demand equations, we expect the estimated coefficients of price, display and feature to be positive. The brand-specific constants should be interpreted as differences relative to a no-purchase alternative, so these terms may be either positive or negative. In the pricing equations, the constant terms in the cost function and the factor price parameters may be either positive or negative.

In Table 2, we see that both the estimated price response coefficient and the feature coefficient in the yogurt category are positive as expected. The coefficients of labor prices are statistically significant for all brands, and the coefficients of ingredient prices are statistically significant for all brands except for Hiland. The estimates of price elasticity of demand have plausible magnitudes, and except for Yoplait, have absolute values greater than 1, a condition consistent with profit-maximizing behavior.

**Table 2 3SLS Parameter Estimates (Standard Errors) for Yogurt Data**

	Estimate
Brand Specific Constants*:	
Dannon	2.488 (0.272)
Yoplait	3.122 (0.352)
Weight Watchers	−0.140 (0.179)
Hiland	0.556 (0.262)
Feature Indicator	0.499 (0.087)
Price (\$ per ounce)	63.977 (3.326)
Constant Term in Cost Function*:	
Dannon	−0.081 (0.042)
Yoplait	0.550 (0.061)
Weight Watchers	−0.079 (0.032)
Hiland	0.264 (0.036)
Mfr. cost: Labor* ( $\times 10^{-2}$ )	
Dannon	0.700 (0.295)
Yoplait	−2.292 (0.426)
Weight Watchers	2.698 (0.224)
Hiland	−1.687 (0.256)
Mfr. cost: Ingredient* ( $\times 10^2$ )	
Dannon	0.092 (0.042)
Yoplait	−0.213 (0.061)
Weight Watchers	−0.123 (0.032)
Hiland	−0.019 (0.036)
Minimized Sum of Squared Errors = 954.66	
Own Price Elasticities	
Dannon	−4.457
Yoplait	−0.875
Weight Watchers	−3.341
Hiland	−4.867

\* Estimated difference with respect to the base "No Purchase."

Table 3 presents the results for catsup for both the standard logit specification and the GEV specification. For the standard logit specification, the estimated price response, feature and display coefficients are all positive and significant. In the pricing equations, the coefficients for labor and container prices are generally significant, while the coefficients for tomato prices are generally insignificant. The results of the GEV estimation are similar. In the demand curves, the estimated price, feature and display coefficients are all positive and significant, and in the pricing equations, the coefficients for labor and container prices are positive and significant, while the coefficients for tomato prices are generally insignificant. The estimate of the within-group correlation co-

efficient  $\sigma$  falls between 0 and 1, as it should, and is significantly different from 0. The estimate of 0.195 indicates a moderate amount of within-group correlation in the 32 ounce size category. The estimated price elasticities are generally plausible, and except for Heinz 28, they have absolute values that are greater than 1.

Recall that the disturbance term in the demand equation in (3) reflects, among other things, unobserved (to

**Table 3 3SLS Parameter Estimates (Standard Errors) for Catsup Data**

	Simple Logit Model	Nested Logit Model
Brand Specific Constants*:		
Heinz 32 oz.	−0.452 (0.211)	−0.089 (0.212)
Hunts 32 oz.	−1.079 (0.206)	−0.596 (0.215)
Heinz 28 oz.	−0.234 (0.248)	0.075 (0.242)
Heinz 44 oz.	−1.798 (0.229)	−1.519 (0.224)
Feature Indicator	0.510 (0.072)	0.439 (0.074)
Display Indicator	0.389 (0.062)	0.290 (0.055)
Price (\$ per ounce)	57.819 (4.781)	63.709 (4.679)
Constant Term in Cost Function*:		
Heinz 32 oz.	−0.411 (0.093)	−0.356 (0.085)
Hunts 32 oz.	−0.393 (0.059)	−0.372 (0.054)
Heinz 28 oz.	−0.793 (0.098)	−0.767 (0.090)
Heinz 44 oz.	−0.222 (0.085)	−0.189 (0.076)
Mfr. cost: Labor* ( $\times 10^2$ )		
Heinz 32 oz.	0.587 (0.249)	0.567 (0.231)
Hunts 32 oz.	0.495 (0.158)	0.455 (0.144)
Heinz 28 oz.	1.010 (0.259)	1.068 (0.238)
Heinz 44 oz.	0.284 (0.226)	0.247 (0.203)
Mfr. cost: Ingredient* ( $\times 10^2$ )		
Heinz 32 oz.	−0.002 (0.003)	0.000 (0.003)
Hunts 32 oz.	0.000 (0.002)	0.000 (0.002)
Heinz 28 oz.	0.000 (0.003)	0.001 (0.003)
Heinz 44 oz.	−0.002 (0.003)	0.000 (0.003)
Mfr. cost: Container Materials* ( $\times 10^2$ )		
Heinz 32 oz.	0.327 (0.075)	0.284 (0.068)
Hunts 32 oz.	0.319 (0.048)	0.308 (0.044)
Heinz 28 oz.	0.639 (0.079)	0.620 (0.073)
Heinz 44 oz.	0.185 (0.069)	0.161 (0.062)
Sigma		0.195 (0.038)
Minimized Sum of Squared Errors	578.466	569.429
Own Price Elasticities		
Heinz 32 oz.	−1.807	−3.523
Hunts 32 oz.	−2.134	−4.257
Heinz 28 oz.	−1.426	−0.657
Heinz 44 oz.	−2.507	−2.609

\* Estimated difference with respect to the base "No Purchase."

the researcher) product attributes, such as coupon availability or national advertising. As shown in Proposition 1, an unobserved product attribute that increases a consumer's willingness to pay, increases the equilibrium wholesale price charged by the manufacturer and the equilibrium retail margin set by the retailer. From an econometric point of view, this creates a positive correlation between prices and the error terms in the demand equations. In a model with linear demand, Madala (1988) shows that when such correlation exists, OLS will bias the estimate of the slope of the demand curve downward. Berry (1994) uses Monte Carlo simulations to show that a downward bias in the price response coefficient can arise in a standard logit model as well. The intuition for these results is that a given increase in price would be accompanied by a positive shock to demand due to the correlation between price and the error, resulting in an estimated smaller than true negative effect of price on demand.

To illustrate the magnitude of the bias, we compare the 3SLS estimate of the price response parameter  $\alpha$  with the SUR estimate. Recall that the 3SLS estimator is consistent when prices are endogenous, while the SUR estimator is inconsistent. In both product categories studied, the SUR estimate is smaller than the 3SLS estimate. In yogurt, the SUR estimate is 26.94, while the 3SLS estimate is 63.98. For catsup, the SUR estimate in the simple logit model is 53.91, while the 3SLS estimate is 57.82. In the GEV specification for catsup, the SUR estimate is 29.54, while the 3SLS estimate is 63.71.

The downward bias in the price response coefficient that we observe is consistent with the empirical evidence in Villas-Boas and Winer (1995) who report a downward bias in two product categories, and with Berry et al. (1995), who report a downward bias in the market for automobiles. Since most empirical studies reported in the literature have been limited to demand-side analyses, we conjecture that price elasticities reported by these studies may be biased downwards. To the extent that such estimates are used by managers for pricing decisions, the downward bias of the SUR estimates would predispose managers to raise prices rather than to lower them.

When a correlation exists between an explanatory variable and an error term, other coefficients in the regression besides the coefficient of the explanatory vari-

able will also be biased. In general, the direction of the bias is difficult to predict. However, in the Monte Carlo simulations reported by Berry (1994), the OLS estimates of the brand-specific constants were biased downward. We obtain a similar finding. In both categories, the SUR estimates of the brand-specific constants are smaller than those from 3SLS.

To the extent that the endogeneity of prices biases the parameter estimates, one might expect that a model that accounts for simultaneity would yield better predictions of brand shares in a hold-out sample than a model that ignores simultaneity. To test this, in both product categories we hold out approximately one-third of the weeks in the sample data for making predictions and estimate the models using the remaining two-thirds. We use the estimation sample to obtain 3SLS estimates of the model. Because market shares of brands and prices are jointly endogenous in our model, predictions of brand shares and prices must be obtained simultaneously. We do this by solving the system of non-linear simultaneous equations in (3) and (12) for every observation in the hold-out sample, given parameter estimates based on the estimation sample and the values of the exogenous variables (factor prices, display, and feature). We compute two summary measures of prediction errors: share-weighted Mean Absolute Percentage Deviation (MAPD), and share-weighted Root Mean Squared Error (RMSE). For comparison, brand share predictions are also made using the SUR estimates that assume prices to be exogenous. In the yogurt data, the MAPD for the 3SLS estimates is smaller than the SUR estimates (0.8168 versus 0.9400), but the RMSE is slightly larger (0.0541 versus 0.0501). In the catsup data, we find the reverse is true. The MAPD for the 3SLS estimates is slightly larger than that for the SUR estimates (0.8416 versus 0.7970), while the RMSE is equal (0.0389 each). This mixed performance of the proposed model in predicting brand shares is not entirely unexpected, since the model simultaneously predicts prices as well, while the benchmark model (SUR estimator) takes prices as exogenously given. In addition, other studies have found that simultaneous equations models in which parameter estimates have been obtained with OLS often predict just as well as when parameters are estimated through more sophisticated methods, even though the OLS estimates are biased (Kennedy 1992).

## 5. Value-Creation and Competitive Advantage

Recent literature on strategy has emphasized the notion that a necessary condition for competitive advantage is superior value creation (Brandenberger and Stuart 1996; Besanko, Dranove, and Shanley 1996). Because the logit demand structure is built upon a foundation of consumer choice, the model of oligopolistic competition with logit demand is a promising framework for exploring the relationship between value-creation and competitive advantage. This is because with logit demand, the value created by an individual brand is summarized by  $v_k - c_k$ , the difference between the “average” consumer’s willingness to pay for brand  $k$  and the cost of producing brand  $k$ . Because we estimate the  $v$ ’s and the  $c$ ’s of brands in each product category, we can explore the extent to which the pattern of market shares and value creation in a product category is consistent with these propositions.

We begin by considering the case in which each manufacturer produces a single brand. For that case we can prove the following result.

**PROPOSITION 2.** *If brand  $j$  creates more value for the average consumer than brand  $k$ , i.e.,  $v_j - c_j > v_k - c_k$ , then at the Nash equilibrium in prices, brand  $j$  will have a larger market share than brand  $k$ , i.e.,  $s_j^* > s_k^*$ . In addition, brand  $j$ ’s profits are higher than brand  $k$ ’s, i.e.,  $\pi_j^* > \pi_k^*$ .*

It is sometimes asserted that when a firm positions itself in the marketplace to achieve competitive advantage, it should attempt to achieve either benefit leadership, which would correspond to having the highest  $v$  in the relevant market, or cost leadership, which would correspond to having the lowest  $c$  in the market. In striving to achieve both, a firm runs the risk of achieving neither and ending up “stuck in the middle” (Porter 1980). Proposition 2 tells us that neither benefit leadership nor cost leadership is a necessary condition for achieving competitive advantage. What is important for equilibrium market shares and operating profits is not the absolute level of  $v$  and  $c$ , but the *difference* between them. There is, however, considerable merit in the argument that the organizational capabilities needed to support a successful “cost strategy” (driving increases in value-creation through reductions in  $c$  over time) dif-

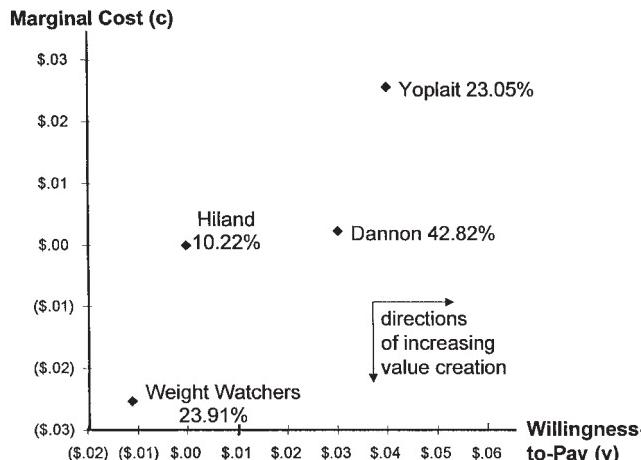
fer from those associated with a successful “benefit strategy” (driving increases in value creation through improvements in  $v$  over time). If so, then one might expect that firms that achieve the highest  $v - c$  are those that either achieve the highest  $v$  or the lowest  $c$ .

Our empirical estimates allow us to explore this question. Figure 1 shows competitive positioning in the Yogurt category, displaying brands according to their relative willingness to pay  $v$  and marginal cost  $c$ .<sup>10</sup> Value-creation increases as one moves to the south-east in Figure 1. In accordance with Proposition 2, the higher is a brand’s value-creation, the higher is its market share. Figure 1 reveals that Dannon is the value-creation leader and (in accordance with Proposition 2), the market share leader as well. Yet, Dannon has neither the lowest cost position nor the highest benefit position in the category: Weight Watchers is the lowest cost brand, while Yoplait is the highest willingness to pay brand. Our empirical evidence on positioning is consistent with anecdotal evidence about the yogurt category: Yoplait has traditionally been seen as a high-quality, premium-priced brand, while Dannon has been viewed as being “synonymous with yogurt.”<sup>11</sup>

Because the expression for  $\pi_j^*$  does not include non-variable costs, such as advertising, nor the firm’s opportunity cost of capital, Proposition 2 does not establish an unambiguous linkage between brand-level value-creation  $v_j - c_j$  and the firm’s overall economic profitability. What the proposition *does show* is that in a product category consisting of single-brand firms, brand-level value-creation  $v_j - c_j$  is unambiguously correlated with equilibrium short-run operating profits  $(p_j^* - c_j)s_j^*H$  (i.e., equilibrium revenues less equilibrium variable production costs). Thus, while differences in value-creation across firms may not fully determine differences in economic profitability across firms, cross-brand differences in value-creation are likely to be a key

<sup>10</sup> Willingness to pay  $v$  is computed by dividing  $\beta_{0k} + \beta X_k$  by  $\alpha$ , where  $X_k$  is evaluated at the sample mean. Marginal cost  $c$  is evaluated at mean value of the factor prices for each brand. Figure 1 shows each brand’s willingness to pay and marginal cost relative to the base brand Hiland.

<sup>11</sup> “General Mills, Inc.: Yoplait Custard Style Yogurt (A),” Harvard Business School Case 9-586-087, 1986.

**Figure 1 Competitive Positioning in the Yogurt Category**

driver of cross-sectional variation in economic profitability in the product category.

Proposition 2 does not extend to the case of multi-brand firms, either with a simple logit demand specification or a nested logit specification. However, there is still an interesting theoretical relationship between value creation, equilibrium market shares, and equilibrium profits in multi-brand firms. As a starting point, define

$$VC_m \equiv \left[ \ln \sum_{i \in I_m} e^{\alpha(v_i - c_i)} \right]$$

to be manufacturer  $m$ 's *inclusive value*. Because  $VC_m = E[\max\{v_i - c_i + \epsilon_{hi} : i \in I_m\}]$ ,  $VC_m$  is the expected value-created of the entire set of manufacturer  $m$ 's brands. With this definition we can prove Proposition 3.

**PROPOSITION 3.** *If manufacturer  $m$ 's inclusive value  $VC_m$  exceeds manufacturer  $o$ 's inclusive value  $VC_o$ , then at the Nash equilibrium, manufacturer  $m$  will have a higher market share and a higher profit than manufacturer  $o$ ; i.e.,  $S_m^* > S_o^*$  and  $\Pi_m^* > \Pi_o^*$ .*

In the catsup category, the market leader Heinz has a large inclusive value relative to its principal competitor, so it is not surprising that Heinz dominates this category. In general, a firm's inclusive value depends both on the number of brands it offers and the value-creation profile of those brands, so one firm might have the high-

est inclusive value in its category simply because it produces more brands than any other firm. The comparison between two multi-brand firms  $m$  and  $o$  becomes most interesting when the firms offer the same number of brands. If so, then a sufficient condition for firm  $m$  to be more profitable than firm  $o$  is that the  $v - c$  of all firm  $m$ 's brands exceeds the  $v - c$  of firm  $o$ 's brands. However, this is not a necessary condition. Indeed, because  $\sum_{i \in I_m} e^{\alpha(v_i - c_i)}$  is a convex function of  $v_i - c_i$ , a firm can have a higher inclusive value than its competitor by having just one brand that creates significantly more value than its competitors' brands despite having a large number of brands that create less value. For example, a three-brand firm whose  $v - cs$  are 80, 10, 10 will have a higher inclusive value ( $VC = 80$ , assuming  $\alpha = 1$ ) than a three-brand firm whose  $v - cs$  are 33.33, 33.33, and 33.33 ( $VC = 34.43$ ). This suggests an 80:20 rule of value creation in a multi-product firm: holding average value-creation fixed across a given number of brands, the greater the disparity between the firm's strongest and weakest brands, the higher is the firm's inclusive value (and thus its equilibrium market share and profit). This result is intuitively sensible. Recall that in a logit discrete choice framework, each consumer acts "as if" it takes a random "draw" from an extreme value distribution to determine the utility for each product in the category and then chooses the single brand that offers it the highest utility. Given this decision framework, a multi-brand firm's ability to create value in the marketplace is related more to its ability to provide one product that is likely to give a large number of consumers a very high utility than to its ability to provide a set of similar brands, each of which offers the possibility of a moderate level of utility.

To summarize, this section shows that the Nash equilibrium in prices implies a set of intuitively appealing relationships between value creation, market share, and profit. Estimating the logit model using an equilibrium perspective allows us not only to explore whether these propositions are observed in the data, but also to examine other empirical questions in competitive strategy such as whether value creation leadership must entail either benefit leadership or cost leadership. With the small number of categories we study here, we cannot provide a definitive answer to this last question. But our two categories are somewhat different. In catsup,

the value-creation leader Heinz 32 is the cost leader but not the benefit leader. In yogurt, by contrast, the value creation leader Dannon is *neither* the cost leader nor the benefit leader. These results suggest a potential richness in the link between positioning, value creation, and competitive advantage in consumer packaged goods that merits further study. Equilibrium-based estimation of the logit model provides a promising basis for such an investigation.

## 6. Summary and Conclusions

This paper presents an empirical study of logit brand choice that explicitly accounts for the endogeneity of prices. Prices are assumed to be determined as a vertical Nash equilibrium among manufacturers and retailers. In equilibrium, unobserved attributes that increase consumers' willingnesses to pay for a brand induce a positive correlation between prices and the error term in the logit demand system. This correlation causes a downward bias in the estimates of the price response coefficient and the brand-specific constants if endogeneity is not explicitly accounted for. We saw evidence of this bias in two product categories: yogurt and catsup.

We then point out that estimating the logit model from an equilibrium perspective has another advantage: by generating estimates of both willingness to pay and costs, we are able to empirically characterize the competitive positions of brands within a product category. The Nash equilibrium in prices when firms face logit demand implies intuitively appealing theoretical propositions about the relationship between market share, profits, and value creation. These results are compatible with the strategic management that emphasizes the link between competitive advantage and value creation. Equilibrium-based logit estimation not only allows one to check whether these propositions are borne out in the data, but it also allows one to investigate whether there are empirical regularities in the competitive positions of market leaders in product categories.

Because our model does not explicitly allow for consumer heterogeneity in brand preferences or in responses to price and other marketing mix variables, one might wonder whether the bias in the price coefficients that we find might be due to consumer heterogeneity

rather than to price endogeneity. To answer this question, we must distinguish between the effect of consumer heterogeneity *when prices are exogenous* and the effect of consumer heterogeneity *when manufacturers and retailers recognize consumer heterogeneity and incorporate it into their pricing decisions*. Recalling that we are working with aggregate (i.e., store-level) data, we know from Allenby and Rossi (1991) that even if consumers' price responses and brand-preferences are heterogeneous, estimating the aggregate logit market share equations with aggregate data will provide unbiased estimates of the means of the price response coefficients as long as all consumers are exposed to the same marketing mix variables.<sup>12</sup> Thus, in the *absence* of endogeneity, the SUR estimates of the share equations in (3) using store-level data should be expected to result in unbiased parameter estimates, and we should not expect to find significant differences in the price response coefficients estimated by SUR and those estimated by 3SLS.

However, when consumers are heterogeneous, and manufacturers and /or retailers recognize that fact and incorporate the demand implications of that heterogeneity into their pricing decisions, then we might expect OLS or SUR estimates to be biased. To illustrate why, suppose that retailers recognize the existence of heterogeneous consumers who differ in their willingness to pay for a particular brand. Retailers then have an incentive to use promotions or sales to price discriminate between high and low willingness-to-pay consumers (Pessendorfer 1996). Returning to the demand function in (3), if we interpret the term  $\beta_{0j} + \xi_{jt}$  as the average (over all consumers) of the brand-specific constant for brand  $j$  that prevails in period  $t$ , then price discrimination by retailers would induce a positive correlation between the retail price and  $\xi_{jt}$ . Periods during which brand  $j$  is on sale would draw a disproportionate number of low willingness-to-pay consumers into the market and push  $\xi_{jt}$  downward. During non-sale periods in which the price of brand  $j$  is higher,  $\xi_{jt}$  would be higher too. This contemporaneous correlation between price and the error term would have the same effect as unobserved product attributes in biasing the estimates of the price response coefficient downward.

<sup>12</sup> This condition holds with respect to in-store prices and promotional conditions in each store-week of the data we use in our analysis.

The preceding discussion suggests that an alternative explanation for the results that we obtain in this paper is the conjunction of consumer heterogeneity and pricing endogeneity. Our aggregate-level analysis cannot distinguish between these alternative explanations. We emphasize, though, that both explanations are ultimately driven by endogenous price setting by manufacturers, by retailers, or by both. In future work, we intend to incorporate the semi-parametric methods of Chintagunta et al. (1991) to estimate logit models with household-level data and heterogeneous consumers in an equilibrium framework. We are hopeful that such an approach will allow us to disentangle the effects of endogeneity coupled with unobserved product attributes from endogeneity coupled with consumer heterogeneity.<sup>13</sup>

<sup>13</sup> An earlier version of this paper was presented at the Marketing Science Conference 1996 and at seminars at Carnegie-Mellon University, Columbia University, Northwestern University, the University of Chicago, and the University of Rochester. The authors would like to acknowledge the helpful comments of Pradeep Chintagunta, Anne Coughlan, David Dranove, Dan Putler, Peter Rossi, an associate editor, and three anonymous referees.

## Appendix. The Nested Logit Specification

In the size-primary nested logit model, there are four groups, indexed by  $g$ , where  $g \in \{0, 28, 32, 44\}$ , and where group 0 contains only the no-purchase alternative. The utility  $u_{hjt}$  of household  $h$  for the  $j$ th brand in group  $g$  on purchase occasion  $t$  is given by

$$u_{hjt} = \beta_{0j} + \beta X_{jt} - \alpha p_{jt} + \xi_{jt} + \zeta_{hgt} + (1 - \sigma)\epsilon_{hjt}, \quad j = 1, \dots, I_g,$$

$$g \in \{0, 28, 32, 44\},$$

where  $I_g$  is the number of brands within group  $g$ ;  $[\zeta_{hgt} + (1 - \sigma)\epsilon_{hjt}]$  is an extreme value random variable, and  $\sigma \in [0, 1]$  is a parameter that measures the within-group correlation of utility levels. If  $\sigma = 0$ , the within-group correlation of utility levels is zero, and we have a standard logit specification. As  $\sigma$  approaches 1, the within-group correlation of utility levels approaches 1. The parameter  $\sigma$  thus measures the "closeness" of brands within a group as compared to brands outside the group.

The demand equation for brand  $j$  can be expressed as a function that is linear in the log of brand  $j$ 's market share:

$$\ln(s_{jt}) = \ln(s_{0t}) + \beta_{0j} + \beta X_{jt} - \alpha p_{jt} + \sigma \ln(\bar{s}_{j|g}) + \xi_{jt}, \quad j = 1, \dots, I_g,$$

$$g \in \{28, 32, 44\}, \quad (\text{A.1})$$

where  $\bar{s}_{j|g}$  is brand  $j$ 's share of sales within group  $g$ . To derive the pricing equations, we find a Nash equilibrium among manufacturers and retailers. As in the simple logit model, the retail markup can be

shown to equal  $1/\alpha s_{0t}^*$ . The wholesale markup, however, differs across brands, reflecting the more complex substitution patterns implied by the nested logit model. Letting the subscripts  $H32$ ,  $H28$ , and  $H44$  denote the three Heinz brands and  $h32$  denote Hunts' 32 ounce brand, the Nash equilibrium pricing equations are as follows:

$$p_{H32t} = c_{H32t} + \frac{1}{\alpha} \left[ \frac{(1 - \sigma)}{(1 - \sigma)(1 - S_{Ht}) + \sigma(1 - \bar{s}_{H32|32t})(1 - s_{H28t} - s_{H44t})} \right] + \frac{1}{s_{0t}^*} + \tau_{H32t}, \quad (\text{A.2})$$

$$p_{H28t} = c_{H28t} + \frac{1}{\alpha} \left[ \frac{(1 - \sigma) + \sigma(1 - \bar{s}_{H32|32t})}{(1 - \sigma)(1 - S_{Ht}) + \sigma(1 - \bar{s}_{H32|32t})(1 - s_{H28t} - s_{H44t})} \right] + \frac{1}{s_{0t}^*} + \tau_{H28t}, \quad (\text{A.3})$$

$$p_{H44t} = c_{H44t} + \frac{1}{\alpha} \left[ \frac{(1 - \sigma) + \sigma(1 - \bar{s}_{H32|32t})}{(1 - \sigma)(1 - S_{Ht}) + \sigma(1 - \bar{s}_{H32|32t})(1 - s_{H28t} - s_{H44t})} \right] + \frac{1}{s_{0t}^*} + \tau_{H44t}, \quad (\text{A.4})$$

$$p_{h32t} = c_{h32t} + \frac{1}{\alpha} \left[ \frac{(1 - \sigma)}{(1 - \sigma)(1 - s_{h32}) + \sigma(1 - \bar{s}_{h32|32t})} \right] + \frac{1}{s_{0t}^*} + \tau_{h32t}, \quad (\text{A.5})$$

where

$$S_{Ht} \equiv s_{H28t} + s_{H32t} + s_{H44t},$$

and

$$\bar{s}_{H32|32t} \equiv \frac{s_{H32t}}{s_{H32t} + s_{h32t}} = 1 - \bar{s}_{h32|32t}.$$

The specification of marginal cost remains as above:  $c_{jt} = \gamma_{0j} + \gamma_j W_t$ . Note that Equations (A.2)–(A.5) reduce to the pricing equation in (8) as  $\sigma$  approaches 0. Note, too, that as  $\sigma$  approaches 1, the retail prices for Heinz 32 and Hunts 32 approach marginal cost. Thus, a high within-group correlation of utility levels implies weak horizontal differentiation among brands within the group.

In estimating this model, Equations (A.1)–(A.5) are treated as a system of simultaneous non-linear equations. We estimate the price response coefficient  $\alpha$ ; brand-specific constants  $\beta_{0j}$ ; coefficients  $\beta$  of the demand-side covariates, feature and display; the parameters  $\gamma$  of the cost function, and the correlation  $\sigma$  of brands within the 32 ounce size category.

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